Climate Action in a World of Complex Ties

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***Abstract*—At a point where the world is diving precipitously into climate collapse, the persistence of global inertia and political voids becomes unacceptable. Understanding what can promote global cooperation to reach climate agreements is essential, where it is imperative to recognize the heterogeneity and inequality that characterize countries and can influence their willingness to contribute. For this purpose, we formulate climate agreements with a game-theoretical metaphor denoted as the Collective-Risk Dilemma. This dilemma recognizes the inherent risk associated with climate disaster and requires a minimum number of contributors to guarantee the effect of collective action. Here we investigate the impact of incorporating heterogeneity in social ties, risk diversity and wealth inequality in the dilemma, resorting to the tools of evolutionary game theory and network science.**

We show that heterogeneity can have different impacts depending on how it is distributed in the network. Our results indicate that risk diversity can significantly enhance cooperation if the central individuals of the network have a high perception of risk. Positively correlating risk, wealth, and centrality is the best arrangement for targets in climate agreements to be met. We further observe that richer individuals and groups should contribute more to maximize cooperation. Accordingly, if the requirements for the different groups are adapted to their capacity, cooperation is improved. Our findings may have implications for policy-making and suggest that the course of the dilemma is strongly dependent on the climate leaders.

***Index Terms*—Climate Action, Social Inequality, Cooperation, Evolutionary Game Theory, Complex Networks**

I. Introduction

Climate change stands as a challenge without precedents in history. There is an urgent need for climate action, and this action requires local and national responses, anchored in a logic of global cooperation [1]. However, in a world full of complex ties, various factors make cooperation difficult to emerge. The climate change problem represents a social dilemma: All countries would benefit if all reduce emissions, nevertheless, a country will individually profit by not reducing. Moreover, the benefits of lowering emissions are not exclusively felt by those who bear the costs of reducing them - everyone shares the profits. As a result, individuals may be tempted to free-ride on the effort of others. Accordingly, this dilemma can be analyzed by resorting to the tools of Game Theory, which represents a mathematical framework capable of formalizing conflict of interests between individuals [2]. In particular, climate agreements can be conveniently formulated as one of the most famous game-theoretical metaphors known as Public Goods Game (PGG) [3].

In a decade where we are surrounded by news constantly alerting us of the immanent irreversibility of climate change, it may appear incomprehensible why global inaction is so prevalent. Consistently, even with the growth of social mobilizations, educational campaigns, or local temperatures getting warmer, the low perception of the risk disaster that remains present was already conceived as one of the Achilles' heels of cooperation in climate settings [4], [5]. Furthermore, the fact that we are contributing in the present to a future with an underlying uncertainty, was proved to be one of the main barriers [6]. On the other hand, it is known that the burden of climate change is not equal to everyone [7]. Fairness principles recurring to historical responsibility for emissions, vulnerability to climate change, and economic capacity are also essential to take into account [8]. Consequently, conflict dynamics between rich and poor parties influence the willingness of individuals to contribute to the agreements and need to be unraveled [9], [10]. It is fundamental to identify the heterogeneity and inequality that characterize countries, which will be worsened with global warming, to push for climate action.

In this work, we focus on capturing the key features of the climate change problem, through the lens of a model capable of analyzing the impact of asymmetries between countries in cooperation dynamics. We investigate the impact of incorporating wealth inequality, risk diversity and heterogeneity in social ties in the climate change dilemma. With this, we intend to more realistically model the predominant differences that persist in climate settings, and contribute to a better comprehension of the conditions under which cooperation in environmental agreements can flourish. For this purpose, we resort to the tools of evolutionary game theory and complex networks, using computer simulations.

In particular, to grasp how cooperation and collective success are influenced by such sources of heterogeneity, we aim to answer the main following questions, regarding the climate change dilemma:

1) What is the impact of correlations between risk and network connectivity?
2) What is the effect of correlations between wealth and network centrality?
3) How can information about network heterogeneity, risk diversity and wealth inequality be combined to leverage cooperation in climate settings?
4) Regarding the distinct classes of wealth, how should the cost of cooperating be distributed?

Concerning the climate change dilemma, it is noteworthy that the usual PGG focuses on providing a collective benefit. However, the climate change problem is concerned with avoiding collective damage, with an inherent uncertainty associated with it. To depict this, the pioneering experiment [4] showed that the essential keys of the global climate change issue can be formalized in terms of a Collective-Risk Dilemma (CRD). This dilemma constitutes a threshold PGG, where a minimum number of contributors are required to avoid a probabilistic loss, and thus collective results vary non-linearly with the number of cooperators. In this work, the process of behavioral adaptation was modeled with a repeated game. Notwithstanding, one can also model this by employing an evolutionary approach in the CRD [5], [11]. With this representation, individuals imitate those who seem more successful, seeking to improve themselves. We formulate our model as a CRD in structured populations, adopting an evolutionary description.

It is worth emphasizing that most of the game-theoretical models assume that individuals are sufficiently equal in the relevant aspects that this framework can grasp. However, this assumption disregards that heterogeneity is ubiquitous around the world. Unraveling symmetries is fundamental to understand the emergence of cooperation [12], [13]. Previous studies have considered heterogeneity in the CRD in social ties by the means of heterogeneous networks [5] and in wealth [10]. Both components were studied separately. Here we introduce variations to the CRD in networked populations, to allow combining various dimensions of heterogeneity. Namely, in terms of social ties, risk perception and wealth, as the effects of combining such sources of heterogeneity remain astray.

II. Model and Methods

Let Z be the size of the population and N the size of the group where the dilemma occurs. Individuals engage with an initial endowment b and can contribute a fraction c of their endowment. If an individual decides to contribute it is designated as a Cooperator (C), otherwise, it is denoted as a Defector (D). To reach success, a minimum number M of contributors is required, where $M \leq N$. Consequently, if a group of size N does not contain M Cs, all members of that group lose their remaining endowments with a probability r that represents the risk of failure. By introducing a coordination threshold where it is necessary to cooperate to reach success, we are capable of mimicking climate negotiations and agreements, that demand a minimum number of contributions to come into practice.

Concerning PGG on networked populations, nodes represent individuals and links define interaction and imitation partners. Individuals participate in games with n direct neighbors, therefore, the number of games that each individual engages in is $n+1$.

We perform simulations to study the evolution of cooperation throughout generations. We consider that individuals start with a strategy s randomly placed on the network, with 50% Cs and 50% Ds (s is set to 0 if D, 1 if C). Strategies are updated asynchronously, meaning that only one individual changes its strategy at a time. In each generation, we select a random node i (with strategy s_i), which in turn randomly selects a random neighbor j, whose strategy s_j imitates with a given probability. This probability is calculated using the imitation function typically employed for finite and structured populations [14]:

$$p = [1 + e^{-\beta(f_j - f_i)}]^{-1}, \qquad (1)$$

where f_j is the fitness of individual j, and f_i is the fitness of individual i. Consequently, imitation will happen with a probability proportional to the fitness difference. The parameter β represents the selection strength - when this constant increases, imitation will depend more on the fitness difference and it is expected that better-performing players will be imitated more often. The fitness of the individuals is the accumulated payoff of all the games in which they engage. An example of a neighborhood defined by a social graph is presented in Figure 1. In the figure, we show the different PGG in which the focal individual (largest sphere) participates. One can interpret these games as the different environmental agreements/negotiations that occur in climate settings.

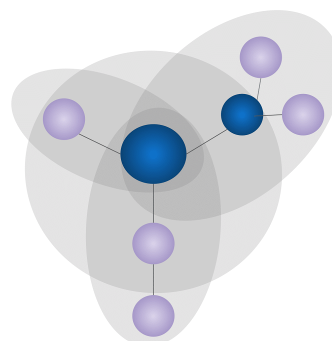

Fig. 1. The focal individual (represented by the largest sphere) participates in distinct groups, each with its own group size. This individual has three direct neighbors ($n = 3$), therefore, it is possible to recognize four groups: one centered in the focal individual and the others in its neighbors. The individual fitness is derived from the accumulated payoff in all four groups [13].

We resort to the following payoff function to consider networked populations, based on the CRD payoff in [5]. Namely, the payoff of an individual y centered in the game of the focal individual x can be written as:

$$P(x, y) = b\{\Theta(k_x - M) + (1-r)[1 - \Theta(k_x - M)]\} - cbs_y, \qquad (2)$$

where $\Theta(x)$ represents the Heaviside step-function distribution, with $\Theta(x) = 0$ if $x < 0$ and $\Theta(x) = 1$ otherwise. We consider $k_x = \sum_{i \in \Omega_x} s_i$, where Ω_x denotes the set constituted by the nodes that are neighbors of x and x itself.

A. Including Risk Heterogeneity

In the previous works, the perception of risk was considered to be equal for all players. However, this might be unrealistic, as some countries have a higher perception of risk and exposure to climate damage than others [15]. To provide a more accurate description of climate agreements, we consider a dichotomy in the risk levels of the population: r_H and r_L representing high and low risks, respectively. We thus consider a population of Z individuals, where Z_H represents the number of individuals with high risk and Z_L constitutes the number of individuals with low risk ($Z_L = Z - Z_H$). In this scenario, the payoff of an individual y centered in the game of the focal individual x can be written as:

$$P_{H/L}(x, y) = b\{\Theta(k_x - M) + (1 - r_y)[1 - \Theta(k_x - M)]\} - cbs_y, \quad (3)$$

with $r_y \in \{r_H, r_L\}$, for individuals with high and low risk, respectively.

B. Including Wealth Inequality

Regarding wealth inequality, to portray the unequal distribution of wealth that persists worldwide, we follow the work [10]. We consider a population of Z individuals, where Z_R represent the rich (provided with an endowment b_R) and $Z_P = Z - Z_R$ constitute the poor (with an endowment b_P, where $b_P < b_R$). Rich Cs contribute with $c_R = cb_R$, whereas poor Cs contribute with $c_P = cb_P$. To consider wealth inequality in networked populations, we assume that the payoff of an individual y that engages in a game centered in the individual x with a group of k_x^R rich Cs, k_x^P poor Cs, and $N - k_x^R - k_x^P$ Ds can be defined as:

$$P_{R/P}(x, y) = b_y\{\Theta(\Delta) + (1 - r)[1 - \Theta(\Delta)]\} - cb_y s_y, \quad (4)$$

with $b_y \in \{b_r, b_p\}$, for rich and poor individuals, respectively. We consider $\Delta = c_R k_x^R + c_P k_x^P - Mc\bar{b}$, where $\bar{b}$ represents the average endowment ($Z\bar{b} = Z_R b_R + Z_P b_P$). Note that in this setting, we require a minimum amount of contributions instead of a minimum number of cooperators, as assumed previously.

C. Networks

To simulate cooperation on networked populations, we resort to the Barabási-Albert Model, one of the most famous models to generate Scale-Free (SF) networks. SF networks illustrate characteristics that are observed empirically. In particular, these networks portray that most individuals only have a few connections, while a minority interacts with many. These minorities are often designated as hubs, stemming from the fact that they represent highly connected nodes. Or in other words, that they have a high centrality [16]. We provide contrasting results with a homogeneous regular network [17], where all individuals are topological equivalent, in Fig. 2b.

D. Simulations

We perform simulations for communities with $Z = 10^3$ individuals and an average group size of $\bar{N} = 7$. The success of a population is measured with the average group achievement, denoted by η_G, which represents the average fractions of groups that can successfully surpass the threshold. We plot the evolution of η_G, averaging the results over 10 different realizations for each type of graph. Each data point corresponds to an average over 500 runs, that is, 50 different realizations of the same class of graph. Each run starts from random initial conditions with 50% Cs and 50% Ds. Each equilibrium group achievement, which represents the stationary state of one run, was obtained by averaging 2000 generations after a transient period of 10^5 generations.

III. Results

A. Heterogeneous Networks

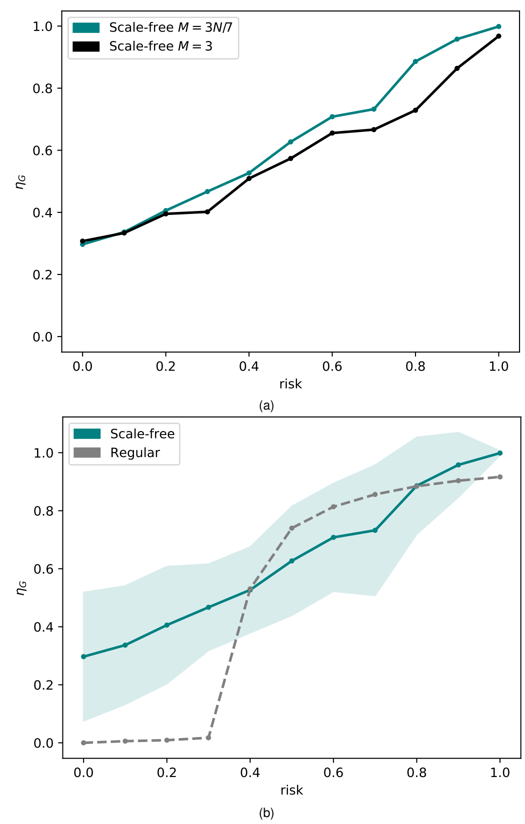

Fig. 2. Group achievement as a function of the risk, considering different networks and distinct thresholds. **(a)** Represents SF networks with two different types of thresholds. In the blue curve: $M = 3N/7$, and in the black curve: $M = 3$. With $M = 3N/7$ we assure that M, on average, is equal in both scenarios. **(b)** Represents the difference between homogeneous regular networks (with $M = 3$) and heterogeneous networks (with $M = 3N/7$). The shaded area illustrates the uncertainty between different simulations that is only present in SF networks. Other parameters: $c = 0.1$, $b = 1$, $\beta = 6.0$.

In this section, we introduce social heterogeneity through the means of heterogeneous graphs. We depict the diversity that is intrinsic to social ties by organizing the population in a SF network, following the work in [5].

Given the complexity introduced with SF networks, where some groups are much bigger than others, it may be reasonable to assume that larger groups might require a larger reduction of emissions. Considering that, we introduce a threshold that is dependent on the number of individuals that take part in the different groups - being an increasing function of N. This is opposed to what is typically assumed, where all groups share the same threshold. In Figure 2a, we illustrate the differences between both thresholds as a function of r. One can observe that considering $M = 3N/7$ has a slightly larger η_G, especially for larger risk values. However, the results suggest that the difference between the two threshold scenarios is not significant. In consonance with the conclusions in [5], assuming a fixed M improves the chances of larger groups achieving success. Nevertheless, smaller groups face stringent requirements, and, consequently, the chances for smaller groups are reduced. The opposite occurs when assuming $M = 3N/7$, as with this threshold it is easier for smaller groups to surpass the threshold. This might explain why the differences between both settings are not significant.

In Figure 2b, we depict the results of considering populations organized in homogeneous regular networks (with $M = 3$) and in SF networks (with the introduced threshold $M = 3N/7$). The curves show the average results of the simulations, and the shaded area corresponds to the standard deviation over the different simulations, which reflects the uncertainty that only emerges in SF networks. One can observe that, even with the high uncertainty present in the heterogeneous scenario, SF networks can open a window of opportunity to cooperation. This is particularly true when the risk is low ($r < 0.4$) or high ($r > 0.8$).

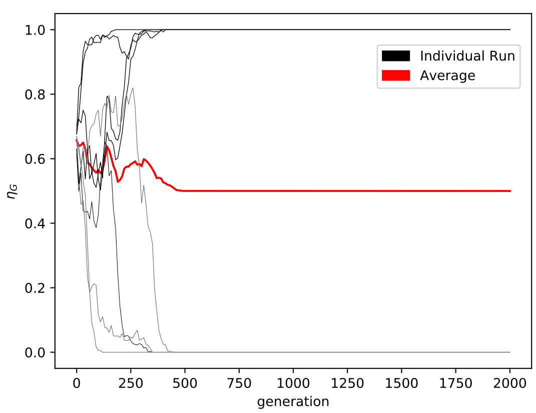

Fig. 3. Time evolution of η_G through generations for 10 runs. The black and grey curves represent individual runs and the red curve corresponds to the average of these runs. The plot was generated considering successive equally spaced points in time (5 to 5 generations). In each run we wait 10^4 generations. Other parameters: $M = 3N/7$, $r = 0.5$, $c = 0.1$, $b = 1$, $\beta = 6.0$.

To better understand the uncertainty that occurs in the heterogeneous case, in Figure 3 we plot the time evolution of η_G through generations. We present ten runs and their average (red curve). One can observe that the system never converges to the average of the simulations. Instead, it is clear the coordination that occurs, where the system always converges to the side of full defection ($\eta_G = 0$) or to full cooperation ($\eta_G = 1$), which is consistent with the conclusions in [18].

We further hypothesize that this uncertainty is present only in SF networks due to the crucial role of the hubs in the evolution of cooperation (that was studied in previous works [13]). In our simulations, their initial strategy is randomly assigned.

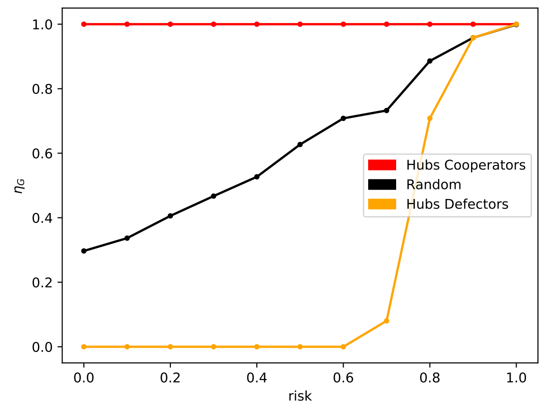

Fig. 4. Group achievement as a function of the risk, considering different setups of the hub's strategies: initializing all hubs as Cs (red curve), all hubs as Ds (orange curve), and randomly assigning the strategy (black curve). Other parameters: $M = 3N/7$, $c = 0.1$, $b = 1$, $\beta = 6.0$.

Consequently, it is natural that when most hubs start as Cs, they can foster the evolution towards cooperative populations. However, when these hubs happen to be Ds, the opposite occurs. We verify our hypothesis, by changing the setup of the hub's strategies in the evolutionary process. In Figure 4, we test two extreme limits to initialize the hub's strategy: one with all hubs as Cs, and the other with all hubs as Ds, maintaining the population with 50% Cs and 50% Ds. One can confirm that the initial strategy of the hubs can have an extreme impact on the population dynamics. To understand this outcome, it is important to stress that hubs are able to accumulate a considerably higher fitness than other nodes, as our model considers accumulated payoffs and they take part in the majority of the games. Hence, hubs will be imitated more effectively and seen as preferential role models, which is in line with what was observed in [19].

To finish this section, it is relevant to emphasize that our results are robust with respect to changes in the intensity of selection β, as one can observe from the results of Figure 5.

B. *Risk Diversity*

In this section, we incorporate risk diversity in the CRD, following the methods described in Section II-A. We test the effects of correlating network connectivity with risk. For this, we divide the population into two halves: one half with high risk (r_H), and the other half with low risk (r_L). We introduce a measure of heterogeneity between high and low risk, denoted by δ. Specifically, we assume that the population has a medium risk $\bar{r}$ (we set $\bar{r} = 0.5$), where the class with high risk has $\bar{r} + \delta$, and the class with low risk has $\bar{r} - \delta$. This implies that the higher the δ, the more diverse is the population. Regarding the correlations, we consider three distinct configurations:

- Positive: the half of the population with high risk corresponds to the nodes with the highest degree, whereas the half with low risk corresponds to the nodes with the lowest degree;

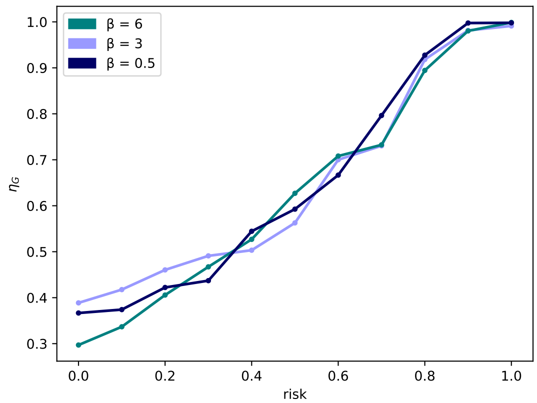

Fig. 5. Group achievement as a function of the risk, considering distinct values of the intensity of selection β. Other parameters: $M = 3N/7$, $c = 0.1$, $b = 1$.

- Negative: the half of the population with high risk corresponds to the nodes with the lowest degree, whereas the half with low risk corresponds to the nodes with the highest degree;
- Random: individuals are randomly assigned to the high or low risk half.

First, we consider the risk as an individual property. In Figure 6a, we present the experiments of varying the heterogeneity in the risk δ, considering the aforementioned correlations. Our findings indicate that risk diversity can have different impacts depending on the correlation we assume. In particular, the positive correlation leads to an impressive enhancement of cooperation, especially when $\delta = 0.4$, where η_G reaches a value of 1. Conversely, the negative correlation significantly decreases the group success. On the other hand, randomly attributing risk levels can marginally improve cooperation.

To grasp the boost of cooperation in the positive correlation, notice that, in this scenario, hubs are associated with a high risk. As it is well-established in the literature, an elevated perception of risk is fundamental to turning players into Cs. Namely, if individuals realize that they have a high risk of disaster, the pressure to cooperate increases. Consequently, hubs will easily cooperate. Given that hubs are connected to the majority of the individuals, they can unleash a wave of cooperation across the whole network, serving as a model for other players to learn that cooperation leads to success. This is particularly true the higher the risk in the hubs (the higher the δ).

By contrast, when hubs face a low perception of risk, the influential role that they have in the network reverts to the scenario where defection prevails.

Regarding the random correlation, the effect turns out to be positive, as it is only necessary to have a few runs in which some hubs are associated with high risk for having a large impact on the average result.

1) Risk at Different Scales: It is worth emphasizing that diversity in risk can emerge in distinct ways, that naturally depend on the interpretation of the network. In Fig. 6a, we embraced diversity as a whole, as we considered the risk to be an individual property. Nevertheless, it is also reasonable to consider risk heterogeneity at other scales. Taking this into consideration, we explore other possibilities by assuming the risk at the level of the games. Considering that a node defines the game centered in itself (see Figure 1), we can interpret the risk of a game to be the risk of the node that defines that game. This setting might reflect, for instance, agreements that are associated with geographical location. Specifically, if we assume that a specific area has a certain risk of failure, all members that are establishing an agreement focused on that area share that same risk. Conversely, the previous setting could reflect agreements that are established by social and political ties that transcend geography, as it is expected that many real-life agreements are formed between countries that do not necessarily share the same risk.

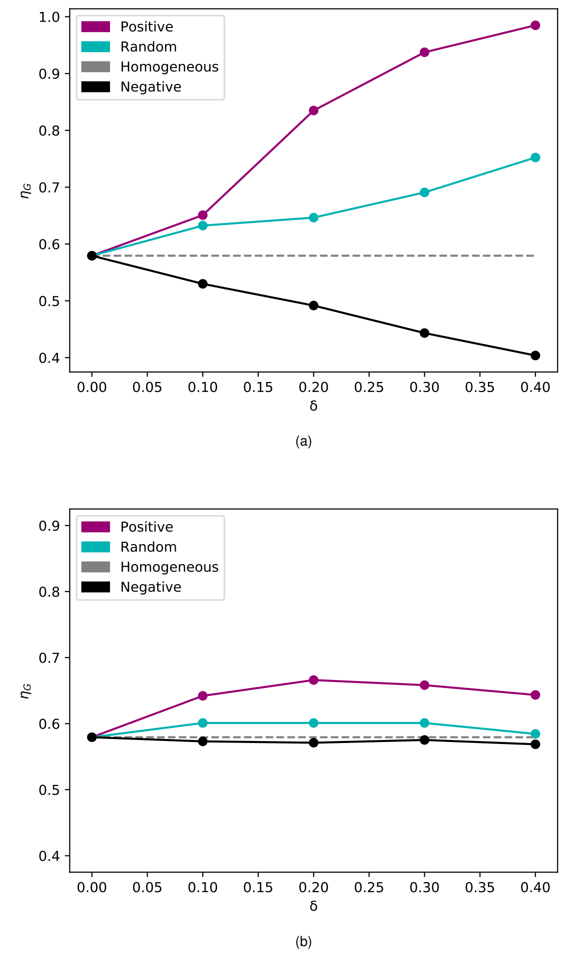

Fig. 6. Group achievement as a function of δ, considering different correlations between risk and connectivity. **(a)** Heterogeneity in the individual risk, where the risk is considered to be an individual propriety in the network. **(b)** Heterogeneity in the risk at the level of the games, where the risk of all individuals participating in a given game is the risk of the focal individual of that game. The dashed grey line represents a reference scenario without risk heterogeneity in SF networks. Other parameters: $M = 3N/7$, $c = 0.1$, $b = 1$, $\beta = 6.0$.

We depict the results of introducing risk diversity in the games in Fig. 6b, by assuming the risk as r_x in the payoff function (3), instead of r_y. It is clear that the impact of considering heterogeneity at the level of the games is not so evident as at the individuals. It should be noted that in Fig. 6b, the risk that hubs face depends on the risk of the different games they engage in. In particular, when the focal individual of the game has a high degree, the risk of the game is $\bar{r}+\delta$, whereas when it has a low degree, the risk is $\bar{r}-\delta$. For instance, let us suppose that a hub is connected to h other hubs and to $n-h$ leaves. In Fig. 6b, the effective risk of the hubs is: $\frac{(\bar{r}+\delta)(h+1)+(\bar{r}-\delta)(n-h)}{n+1}$. Conversely, in Fig. 6a, the hubs engage in the games with an effective risk of $\bar{r}+\delta$. Given that, in setting 6b, h is always less than n, as hubs are connected to the majority of the individuals and SF networks have significantly more low-degree nodes, it is possible to infer that the effective risk of the hubs in the agreements will always be higher when the risk is individual. This confers an advantage for hubs to cooperate in the evolutionary process, which significantly enhances the chances for global cooperation in that scenario.

Similarly, when we assume a negative correlation, the difference between the two scenarios follows the reasoning explained above: In Fig. 6b, the hubs engage in the games with an effective risk that will be composed of high and low risks, whereas in Fig. 6a, it will be constituted only by low risks, and, consequently, will amplify the deteriorating effect that a low risk has on the evolution of cooperation.

Notice that the impact of δ is also different in the two schemes. In Fig. 6a, the effect of increasing the risk heterogeneity enhances the effect of the correlations, whereas, in Fig. 6b, it does not seem as significant. Naturally, when one considers the individual risk, increasing δ, directly increases the effective risk that hubs confront in their games. Contrarily, when the risk is at the level of the games, increasing δ does not increase the effective risk that hubs face in their agreements. In particular, although increasing risk diversity increases the risk of games centered in highly connected nodes, it also decreases the risk of games centered in low degree nodes. Therefore, the impact of δ is not considerable.

Considering the plethora of options in this dilemma, it is plausible that climate agreements may fall somewhere between these two scenarios, as the agreements can be established focused both on specific regions and other characteristics that exceed geography. For simplicity, thereafter we consider the risk as an individual property when introducing risk diversity.

2) The Impact of Major Hubs: Now, we investigate how many hubs with high risk are necessary for cooperation to thrive. For this, we assign a high risk (r_H) to Z_H top connected hubs. The remaining nodes are assigned with a risk x, to maintain the average risk per individual in the network $\bar{r}$ (we consider $\bar{r}=0.5$). The value for x can be calculated as follows:

$$x=\frac{\bar{r}Z-r_H Z_H}{Z-Z_H}. \tag{5}$$

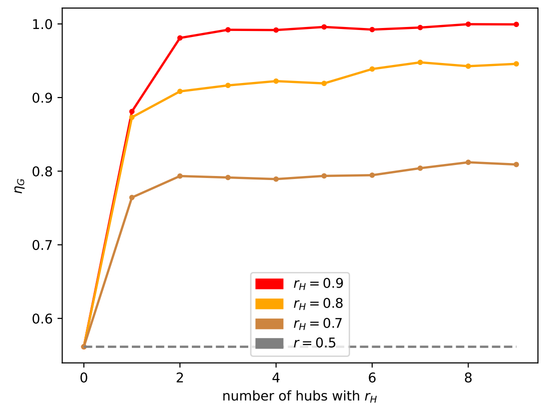

Fig. 7. Group achievement as a function of the number of high-risk hubs, for several high-risk levels. The hubs are ordered by descent connectivity. Other parameters: $M=3N/7$, $c=0.1$, $b=1$, $\beta=6.0$, $\bar{r}=0.5$.

In Figure 7, we vary the number of high-risk hubs, ordered by descent connectivity, for several high-risk levels. We observe that cooperation becomes viable by only assigning a high risk to a few major hubs. This is especially notable when $r_H=0.9$. Overall, the results of Figure 7 suggest that, even when the average risk on the population is not significant ($\bar{r}=0.5$), it is only necessary to adjust the perception of risk on some few individuals that have higher connectivity to turn cooperation into the dominant strategy.

C. Wealth Inequality

In this section, we incorporate wealth inequality by considering that the population is constituted of 20% rich individuals and 80% poor, as detailed in Section II-B. We focus on understanding the impacts of correlating wealth with connectivity. For this, we examine three distinct correlations:

- Positive: the 20% rich will be constituted by the 20% nodes with the highest degree, and the 80% poor will be composed by the remaining nodes;
- Negative: the 20% rich will be formed by the 20% nodes with the lowest degree, and the 80% poor will be composed by the remaining nodes;
- Random: we randomly attribute the wealth levels in the network, maintaining the 20%-80% distribution of wealth.

We perform experiments to analyze the impact of considering the different correlations, varying the b_r. We define $b_p=\frac{Z-Z_r b_r}{Z_p}$, to maintain the same average endowment of the population ($\bar{b}=1$). The results are depicted in Figure 8. Note that, along the x-axis, the wealth inequality increases, with the rich becoming richer and the poor becoming poorer.

Subsequently, to combine risk diversity with wealth inequality and social heterogeneity, we adjust the risk of a few major hubs in Figure 9, assuming distinct correlations between wealth and connectivity (positive and negative). In particular, we consider two scenario regarding the risk: one

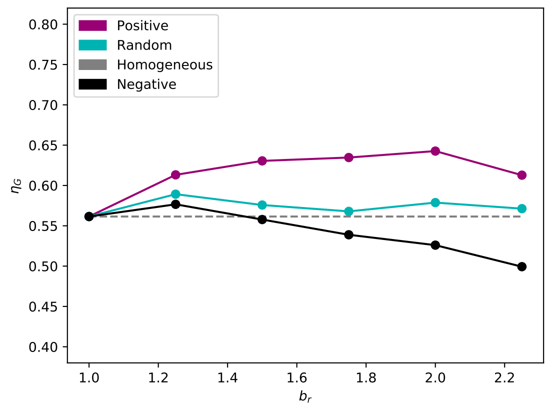

Fig. 8. Group achievement as a function of the endowment of the rich b_r, considering different correlations between wealth and connectivity. The dashed grey line represents a reference scenario without wealth inequality in SF nets. Other parameters: $M = 4N/7$, $\bar{r} = 0.5$, $c = 0.1$, $\beta = 6.0$, $\bar{b} = 1$.

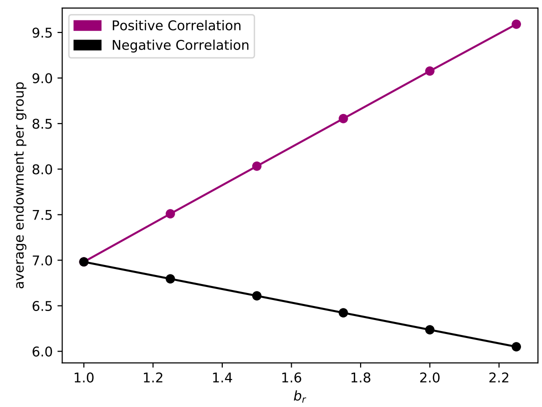

Fig. 10. Average endowment available per group in the network as a function of b_r, considering distinct correlations between wealth and connectivity. Each data point is the average over 10 different SF nets. Other parameters: $\bar{b} = 1$.

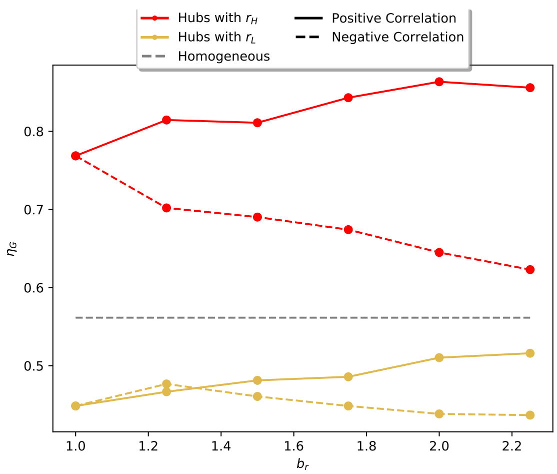

Fig. 9. Group achievement as a function of b_r, combining risk, wealth and connectivity. The red curves correspond to 7 hubs with $r_H = 0.7$, and the yellow curves represent 7 hubs with $r_L = 0.3$. The solid curves correspond to a positive correlation between wealth and connectivity, whereas the dashed coloured curves represent a negative correlation. The grey dashed line is the homogeneous case, without heterogeneity in risk or wealth in SF networks. Other parameters: $M = 4N/7$, $\bar{r} = 0.5$, $\delta = 0.2$, $c = 0.1$, $\beta = 6.0$, $\bar{b} = 1$.

with $r_H = 0.7$ in 7 major hubs (red curves) and the other with $r_L = 0.3$ in 7 major hubs (yellow curves).

The results of both figures indicate that the positive correlation between wealth and connectivity is the one that confers the highest values of η_G, whereas the negative one provides the lowest. A possible reason for this relates to the properties of SF networks. Notice that, even if we ensure that the average endowment per individual is constant in comparison to the homogeneous case ($\bar{b} = 1$), as nodes are distributed heterogeneously in the network, the wealth available per game is modified. To better grasp the effect that increasing wealth disparities has on the budget available to the population, in Figure 10 we illustrate the impact of increasing b_r (and, consequently, decreasing b_p) in the average endowment available per group. We can observe that when b_r increases, the amount available per group on average increases in the positive correlation and decreases in the negative one. Accordingly, by positioning rich individuals in the majority of the games (positive correlation), b_r is considered in most of the agreements. Consequently, we are increasing the capacity available per group in the network. This increases the chances of having the demanded amount of contributions to surpass the threshold. By contrast, when the rich only take part in a few games (negative correlation), the capacity available per group in the population decreases and reduces the chances of success.

Hence, our results indicate that SF networks and the way that wealth is distributed among the different games - that is a direct consequence of the network - provides greater diversity in the investments available to the population. As a result, heterogeneity can have opposite effects depending on the position where rich and poor are in the network.

This conclusion is similar to the one obtained regarding the impact of risk diversity. Nevertheless, it is noteworthy that if one compares Figure 8 (with wealth inequality only), the highest value of η_G is around 0.65, whereas, in Figure 6a (with risk diversity only), there is a significant improvement, with η_G reaching 1. This indicates that risk heterogeneity may be more impactful than wealth inequality.

Regarding the effect of incorporating risk heterogeneity in Figure 9, one can observe that having hubs with high risk is essential to achieve environmental agreements. Correspondingly, even when hubs are rich, success is not feasible if they have a low perception of risk (yellow solid curve).

Besides, one can observe that when hubs have a high risk, the impact of the correlations between wealth and connectivity are more notable than when they have a low risk. As we have seen before, when hubs face a low risk they influence the network towards defective behavior. Therefore, there is not much difference between hubs having a large available amount (as in the positive correlation) or a small amount (negative correlation), as it is most likely that many individuals will not cooperate in both correlations. Conversely, when hubs have a high perception of risk and influence the population to cooperate, surpassing the threshold strongly depends on the amount available to contribute.

Overall, we can observe that cooperation is improved when centrality is positively correlated with risk. This effect is amplified whenever risk and centrality are positively correlated with individuals' wealth. Summarizing, we can infer that the best arrangement between the multiple sources of heterogeneity is to positively align centrality, risk and wealth.

1) Discussion of the Correlations: Given these results, it is natural to ask how wealth, risk and connectivity are correlated in the real world. Are the hubs of climate agreements rich and with a higher perception of risk or is the scenario the opposite? To discuss how realistic the correlations are, we focus on analyzing the perception of risk and wealth of the countries leading the environmental negotiations - the hubs of the network. According to [20], the EU, USA and China are undoubtedly the climate change leaders, which we can interpret as the major hubs. Moreover, we can also consider as hubs the Group of Seven (G7) - that wield significant international influence. Regarding the perception of risk, it is hard to grasp how the correlation should be. However, climate leaders usually have a low perception of risk [7], [15]. On the other hand, in real environmental agreements, the hubs actually tend to be rich. For instance, the G7 is considered to be composed of the seven wealthiest advanced countries [21]. Having said that, it is likely that the most realistic combination between centrality, wealth and risk is the one where hubs are rich but have a low perception of risk. In Figure 9, it is observable that in this setting (yellow solid curve) group success is not feasible. The course of this demanding problem seems to essentially depend on the hubs and their perception of risk. It is crucial that the leaders recognize their profound responsibility and act in accordance, otherwise, the tragedy of the commons is inevitable.

2) Including Fairness Notions: It is known that one of the causes for previous failures to reach climate agreements is due to conflicting policies between rich and poor [8]. Understanding how the cooperation cost should be distributed among the two classes results in a fairness dilemma. Respectively, there is not a consensus on how rich and poor should contribute to climate negotiations: Should the rich and the poor invest the same amount? Or should the rich contribute more?

2.1) At the Individual Level: In the former section, we considered that the contributions of individuals were proportional to their wealth, being a relative value. Here, we investigate what happens when the two classes contribute an absolute amount, equal for both of them. In particular, in the former setting, rich individuals have a contribution of $c_r = cb_r$ and poor individuals of $c_p = cb_p$. In the latter setting, both have the same contribution, that is, $c_r = c_p = 0.1$.

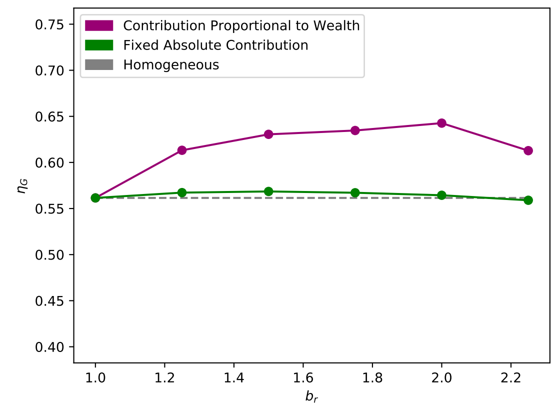

Fig. 11. Group achievement as a function of b_r, considering two distinct ways of contributions: in the purple curve contribution is proportional to wealth, which means that rich contribute more than poor; in the green curve, the contribution is fixed for the two wealth classes, meaning that rich and poor contribute the same absolute terms. Other parameters: $M = 4N/7$, $\bar{r} = 0.5$, $\beta = 6.0$, $\bar{b} = 1$.

In Figure 11, we show the effects of considering the two contribution scenarios previously explained. We can observe that cooperation is more viable when the rich contribute larger amounts than the poor (purple curve). Observe that, the increase in the capacity available when hubs are rich (that we observed in Figure 10) does not remain valid if they do not contribute proportionally to their wealth. As a result, when the contributions are equal, the chances of having the necessary amount of contributions to surpass the threshold do not increase, and there is no improvement in group success.

2.2) At the Group Level: Until this point, we demanded the same amount of contributions irrespective of the wealth composition of the groups. However, requiring the same contributions from a group composed of N rich countries and a group of N poor countries might not be a fair assumption. Taking this into consideration, here we study the differences in collective success when we consider: *1)* a threshold that is agnostic to inequality (as considered previously) and *2)* a threshold that defines success in a more fair measure and discriminates the wealth of the individuals in groups. For the latter setting, instead of calculating the threshold factor M of a group regarding the number of individuals that take part in that group, we consider the amount of contribution that is available in the group. Specifically, to calculate the threshold of a group i, which corresponds to $M_i c\bar{b}$, we assume $M_i = 4 \times \frac{Ci}{\bar{C}}$, where C_i is the contribution capacity available in group i and $\bar{C}$ the average contribution capacity per group in the network. This is opposed to what was being assumed, where $M_i = 4 \times \frac{N_i}{N} = 4 \times \frac{N_i}{7}$. The outcomes of considering the distinct thresholds are depicted in Figure 12.

Our results indicate that the wealth-dependent threshold promotes cooperation. Accordingly, in this scenario, the effort rate of the groups is being considered, as we are requiring that groups contribute an amount based on what they can

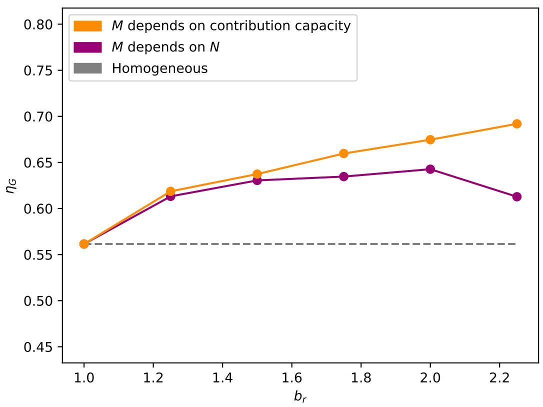

Fig. 12. Group achievement as a function of b_r, considering different types of thresholds: the orange curve corresponds to a threshold that increases with the contribution capacity of the groups, whereas in the purple curve the threshold increases with the group size and ignores the group contribution capacity. Other parameters: $\bar{r} = 0.5$, $c = 0.1$, $\beta = 6.0$, $\bar{b} = 1$.

contribute. By contrast, in the threshold that ignores the composition of the groups, this effort is disregarded. As a result, when the poor get significantly poor in this setting (as in $b_r = 2.25$), there will be many groups with mostly poor individuals that face severe requirements, given that they have a small available budget to contribute. In these groups, even if poor individuals cooperate, it is extremely difficult to achieve the threshold, which naturally affects the global success in the network. This negative effect can be alleviated if we recognize the capacity available in the groups. Specifically, when the threshold considers the wealth composition of the groups, we are lowering the threshold in poorer groups (as their available capacity is inferior). Given that we are considering that 80% of individuals are poor, the majority of the groups will be poorer (which is verified in Figure 13). Therefore, there will be considerably more groups that will find it easier to surpass the requirements.

The results of Figure 12 essentially suggest that it is easier to reach group success if the collective goals are adjusted to the effort and capacity of each group. This is complementary to the outcome of Figure 11, as it indicates that, in order to maximize cooperation, those who have more wealth should contribute more - which can be applied to individuals or groups.

IV. Conclusion

In this work, we propose to contribute to a deeper understanding of the factors under which cooperation in climate settings can prosper. For this, we resorted to an evolutionary approach, recurring to complex networks.

We tackled the challenge of unraveling symmetries in the climate change dilemma, focusing on incorporating heterogeneity in social ties, risk diversity, and wealth inequality - which impacts remain astray in the literature. In order to answer our main research questions and to portray a more accurate description of environmental agreements, we developed a model that allows for different sources of heterogeneity, by introducing variations in the CRD.

We start by conferring a more realistic representation of environmental agreements by including social heterogeneity in the dilemma through SF networks. Our results suggest that organizing the population in a heterogeneous network can open a window of opportunity for cooperation. However, there is a lot of uncertainty associated with the results we obtained. We inferred that this uncertainty is rooted in the behavior of the hubs, with the chance of overall success of the population being strongly influenced by the initial strategy of these individuals.

Subsequently, we incorporated risk diversity. Our results indicate that heterogeneity exhibits distinct effects depending on how we correlate risk with connectivity. In particular, we found that assuming a positive correlation between individual risk and centrality can unleash a wave of cooperation in the network. This is particularly true the higher the heterogeneity we consider, i.e, the more accentuated is the difference between high and low risks in the population. We further observed that assuring that some few highly central players are assigned with a high perception of risk is enough to nudge an entire population into cooperation.

Following that, we included wealth inequality in the dilemma. Similar to the conclusions we obtained previously, we found that heterogeneity in wealth has opposite effects depending on the correlation between wealth and degree that is considered. Our results indicate that assuming a positive correlation increases the chances of achieving global cooperation. Notwithstanding, through our simulations, we observed that risk diversity appears to be more impactful than wealth inequality. When merging these three dimensions of heterogeneity in the dilemma, we observed that the positive effect of correlating risk with centrality is enhanced whenever risk and centrality are positively correlated with individuals' wealth. In other words, assuming that hubs have more to contribute and have a high perception of risk is the arrangement that provides better results.

Lastly, we explored the impact of considering distinct fairness notions, regarding wealth inequality. In particular, we investigated how the cost of cooperating should be allocated to improve the chances of achieving climate agreements. Our findings show that richer individuals should contribute more to improve cooperation. To analyze fairness at a group level, we proposed a new threshold capable of embracing the complexity introduced when considering wealth inequality in SF networks. We concluded that cooperation is fostered if the collective goals are adjusted to the effort and capacity of each group, where richer groups should contribute more.

It is noteworthy that our results may have implications for policy-making and suggest that the course of this demanding problem is strongly dependent on the hubs - the climate leaders.

In our model, we disentangled symmetries that are typically assumed when modeling social dilemmas. Nonetheless, certain assumptions we made remained unexplored. For instance, the

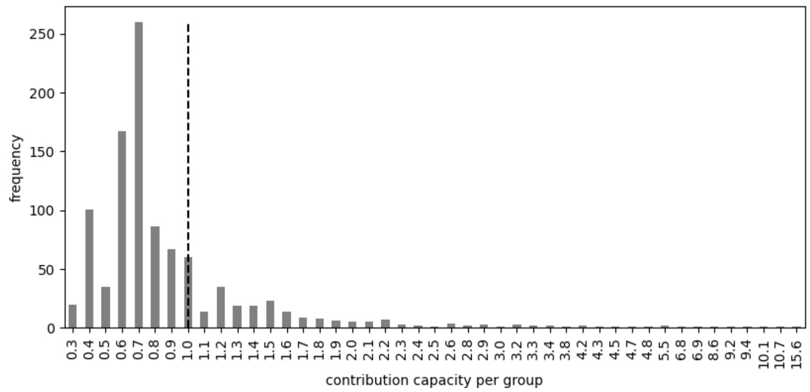

Fig. 13. Frequency of the contribution capacity per group, considering $b_r = 2.25$, $b_p = 0.6875$. For visual clarity, we present the contribution per group in a rounded format for a illustrative SF network. The dashed black line represents the average contribution per group. Portraying wealth inequality in SF networks results in a distribution of wealth where the majority of the groups are poorer, whereas a minority is richer. Specifically, we verified that 77.7% of the groups had an available capacity smaller than the average capacity. Other parameters: $c = 0.1$, $\bar{b} = 1$.

Barabási-Albert Model has some limitations. Other more realist complex networks could be considered, as the Dorogovtsev-Goltsev-Mendes Minimal Model [22], which generates highly clustered SF networks. Moreover, instead of only considering interaction in pairs, hypergraphs [23] provide a mathematical framework capable of representing interactions between larger groupings. On the other hand, instead of assuming binary risk and wealth levels, it could be of importance to analyze intermediate levels. Regarding mechanisms that focus on cooperative relationships, studying the impacts of monitoring institutions [24], [25] or financial incentives [26] could provide influential contributions.

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